MACHINE LEARNING (ML) FOR TRACKING THE GEO-TEMPORALITY OF A TREND: DOCUMENTING THE FREQUENCY OF THE BASEBALL-TRUCKER HAT ON SOCIAL MEDIA AND THE RUNWAY

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ABSTRACT

This study applied fine-grained Machine Learning (ML) to document the frequency of baseball-trucker hats on social media with images populated from the Matzen et al. (2017) *StreetStyle-27k* Instagram dataset (2013-2016) and as produced in runway shows for the luxury market with images populated from the *Vogue Runway* database (2000-2018). The results show a low frequency of baseball-trucker hats on social media from 2013-2016 with little annual fluctuation. The *Vogue Runway* plots showed that baseball-hats appeared on the runway before 2008 with a slow but steady annual increase from 2008 through 2018 with a spike in 2016 to 2017. The trend is discussed within the context of social, cultural, and economic factors. Although ML requires refinement, its use as a tool to document and analyze increasingly complex trends is promising for scholars. The study shows one implementation of high-level concept recognition to map the geo-temporality of a fashion trend.

BIOGRAPHICAL SKETCH

Rachel R. Getman holds a bachelor's degree in Anthropology from the University of California at Los Angeles (UCLA). Her interests lie in the intersection of arts and sciences through interdisciplinary collaboration. The diversification of her professional experience from the service industry, education, wardrobe styling, apparel production, commercial vocals, and organic agriculture influence her advocacy for holistic thinking and non-linear problem solving. Perpetually list-making and knolling, she considers herself an expert in the field of applied neurotics.

To David A. Getman

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LIST OF ABBREVIATIONS

Computer Science (CS)

Fashion Studies (FS)

Machine Learning (ML)

Deep Learning (DL)

Artificial Neural Network (ANN)

CHAPTER 1

INTRODUCTION

The ubiquity of smart phones, social media platforms, and networking sites provide billions of world-wide users the tools to capture and share the minutia of their everyday lives. Digital data acquired from these platforms have arguably become one of the most valuable resources and commodities of the 21st Century. *The Economist* (2017) compared the value of data to that of oil for the previous century, calling it the "fuel of the future" in the data economy ("Fuel of the Future," 2017). Not unlike oil in its extraction, refinement, and commodification in the global market, digital data has resulted in the creation of new infrastructure and monopolies ("Fuel of the Future," 2017). Organizations and researchers covet user information, bi-products of the internet boom and digital age, and often obtain data from social media and e-commerce platforms when trying to tap markets and make cultural predictions.

Machine learning (ML) provides the technology to recognize patterns and analyze large image datasets through algorithmic models. Although ML requires refinement, its use as a tool to document and analyze increasingly complex trends shows promise. It is likely as scientists refine ML technology, its adoption across disciplines and industries will dramatically increase and become ubiquitous. Documenting and describing peaks and valleys in the geo-temporality of a trend can potentially help researchers understand the social implications of trend popularity and the potential interaction with concurrent socio-cultural events.

This study applied fine-grained ML for pattern recognition and visualizing trend frequency of baseball-trucker hats, building on Matzen et al.'s (2017) framework for visual trend discovery to analyze clothing and style in large image datasets (Matzen et al., 2017). As a collaborative study between Fashion Scholars (FS) and Computer Scientists (CS), this research illustrated the value of interdisciplinary projects. The author chronicled the frequency of baseball-trucker hats on international fashion runways and in several cities in the United States using two large image datasets populated with images from the *Vogue Runway* database (2000-2018) and the Matzen et al. (2017) *Instagram* dataset (2013-2016) to evaluate the movement and relationship of the hat's distribution on luxury runways and social media (Matzen et al. 2017). The CS researchers built the machine learning technology by creating annotators and classifiers while the author provided the research questions and interpreted the results and findings. The study shows one implementation of high-level concept recognition to map the geo-temporality of the baseball-trucker hat. Tracking the frequency of the trend helps visualize larger patterns in fashion trends and cultural shifts while creating socio-historical records of aesthetics for academia and the fashion industry.

Computer scientists have used fashion as a domain to develop technology for sales forecasting, supply-chain management, e-commerce personalization, and manufacturing, although little research has applied the ML technology to historical and cultural analysis of fashion trends in the social sciences (Guo et al., 2010; Tokumaru and Muranaka, 2008; Cardoso et. al, 2018; Takagi et. al 2017). The disparity of studies and publications among the fields of CS and application of ML for

FS shows a promising contribution to the field of FS. Applying advancing technology to the socio-historical understanding of fashion trends and cultural change may help with the analysis of big data retrieved from social media and digitization of images whether online or in databases not previously used in historical fashion analysis.

The shared desire to advance and implement ML and computer vision in the fashion domain provides a unique opportunity for a symbiotic interdisciplinary inquiry. Quantifying fashion change through pattern recognition is a promising tool for social scientists and industry professionals in understanding larger fashion trends. Through ML, researchers may analyze millions of images in large datasets, recognize patterns in pixelated digital images beyond the capability of the human eye through statistical analysis and probability allowing researchers to visualize cultural change.

Trends, Fads, and Microtrends

When examining the collective adoption of an accessory such as the baseball-trucker hat by tracking its emergence on the luxury runways and social media it is important to define a trend. A trend in the context of this study is defined as a collective popularity of a fashion aesthetic, lifestyle, or phenomenon over a period of time. Distinguishing between a trend and fad is nebulous, however, in this study a fad is defines as similar to a trend in its collective popularity, however shorter in time, smaller in scale.

For centuries scholars have developed theories to explain the why group develop similar preferences for objects, styles, colors, lifestyles, and phenomenon. Sociologist Herbert Blumer (1969) attributed the of modernity as a factor for individuals to collectively choose one fashion style in turn creating a trend (Blumer, 1969). Blumer (1969) argued that especially during times of chaos or uncertainty in a changing modern society, individuals align with others to cope with uncertainty and find community through shared interest or style (Blumer, 1969). Increased globalization and access to information potentially leads to a rise in concurrent trends and fads and rapid cycling.

Political Strategist Mark Penn (2007) and Kinney Zalesne (2007) argued for a rise in “microtrends” or smaller forces that are simultaneously popular within a smaller percentage of the population but together create changes in society (Penn and Zalesne, 2007). Penn and Zalensne (2007) attributed the ability of microtrends to influence larger movements to the advent of the internet, digitization, and globalization, as well as, to an increase in choice and personalization (Penn and Zalesne, 2007). Through micro trends, smaller groups of individuals selecting a food, fashion style, or phenomenon can trigger a popular movement or niche market (Penn and Zalesne, 2007).

Purpose of the Thesis

The purpose of this study is to utilize the resources of large image datasets in documenting and visualizing the baseball-trucker hat trend while showing the value of interdisciplinary research between the science and humanities. The ability to quantify trends and document the movement of fashion objects enriches socio-historical analysis and the understanding of fashion change. This research offers a methodology for applying ML to analyzing fashion change geo-temporally: meaning by location geographically over time. The study shows one implementation of high-level concept recognition to map the geo-temporality of a fashion trend. Applying ML to a socio-cultural analysis can potentially contribute to the development of new theory and evaluation of foundational work.

Machine Learning

Machine Learning (ML) is a subset of Artificial Intelligence (AI) in which software engineers program computers with algorithmic inputs to learn specific tasks without explicit programming (Rogelberg, 2017). AI is a field within CS in which scientists program computers through mathematical algorithmic formulas to perform human tasks (Butterfield and Ngondi, 2016). In ML computers learn to perform tasks through a "training" dataset with the tasks the programmers want the system to perform (Loudras and Ebert, 2016). Computer vision is a subfield of ML that programs computers to understand and analyze information from digital images or videos (Haaxma-Jurek, 2014). Deep learning (DL) is a subset of ML that specifically layers algorithms to create Artificial Neural Networks (ANN) that perform computer functions (Jordan and Mitchell, 2015). ANNs were designed to mimic the neurological network of the human brain to process information (Wu and Feng, 2018). In other words, programmers are trying to build artificial brains to process information, imitating the way human brains process stimulus in the physical world.

Terminology

The fashion object chronicled in this study--- the baseball-trucker hat---has a variety of popular names: "baseball cap," "baseball hat," "cap," or by other stylistic variations including "trucker hat," "gimme cap," or "company cap" (Kelly, 2018; Lilifors, 2009; Moore, 2016). To include both the baseball and trucker styles, this study will refer to the hat as a *baseball-trucker* hat.

CHAPTER 2

REVIEW OF LITERATURE

Quantifying Fashion Change and Socio-Cultural Phenomenon

Understanding fashion change over time and the relationship to cultural phenomena became an area of interest to several social scientists in the late 19^{th} and 20^{th} centuries. Sociologist Georg Simmel (1904) wrote about dual processes of imitation and differentiation as promulgators of fashion change, while Psychologist John Carl Flügel (1966) used a psychoanalytical framework to draw connections between fashion change and economic prosperity (Simmel, 1904; Flügel, 1966). Flügel connected economic growth to rapid stylistic change while claiming economic struggle inhibited changes in fashion (Flügel, 1966).

James Laver (1945), Fashion Theorist and Victoria and Albert Museum Costume Keeper (equivalent to collections manager) from 1938-1959, created a list of laws, commonly known as "Laver's Law," to understand cyclical change (Laver, 1945). Laver (1945) paired twelve adjectives including "indecent", "shameless", "outre" (daring), "smart", "dowdy", and "hideous", with the number of years before or after the trend was stylish to describe fashion trends (Laver, 1945). For instance, a garment might be "indecent" ten years before its time, "daring" one year before being on trend, "hideous" 10 years after its time while "beautiful" 150 years later (Laver, 1945). Laver's Laws influenced fashion buyers including Stanley Marcus, president of

Neiman Marcus in the 1960s, who often consulted Laver for trend forecasting advice (Marcus, 2001).

Anthropologists Alfred Kroeber (1940) and Jane Richardson (1940) applied a quantitative approach to understand fashion change. Krober (1940) and Richardson (1940) manually measured changes in fashion styles (e.g. hemlines, waistlines, and décolletage) in fashion plate illustrations, comparing the patterns of change to concurrent political unrest (Richardson and Kroeber, 1940). Their scholarly inquiry attempted to quantify fashion change through changing silhouettes and to define the relationship between fashion styles and political forces. A major challenge not acknowledged by Kroeber and Richardson was the variability of hand drawn fashion plates, since illustrations are only suggestive of garment silhouette.

After Kroeber (1940) and Richardson's (1940) initial study several social scientists attempted to contribute to and extend the methods with increased accuracy through mathematical modeling. Sociologists Nancy Jack (1948) and Betty Schiffer (1948) built upon Kroeber's methods using photographs instead of drawings from fashion publications to quantify and visualize fashion change (Jack and Schiffer, 1948). Anthropologists John Lowe (1982) and Elizabeth Lowe (1982) applied a mathematical model to analyze historical fashion data of women's evening dresses from 1789 to 1935 and tested the results against new data extending to 1983 to determine its predictability (Lowe and Lowe, 1982). With advancements in ML, scholars can now further this mode of inquiry with intelligent models and use computer vision's precision to document patterns of dress in larger datasets. The application of ML can help scholars understand the relationship between fashion change, trend adoption, and socio-cultural phenomenon.

Fashion historian Jo B. Paoletti (1982) applied a content analysis to the study of historic costume to understand stylistic fashion change over time. She implemented a systematic and methodical approach, analyzing data from multiple sources through hand or computer sorting combined with descriptive or inferential statistics (Paoletti, 1982). At a time when few costume historians used content analysis, Paoletti employed the method in a comparative study of women's dress from 1875-1885 and in a comparison of men's and women's garment cartoons from 1880 – 1910 (Paoletti, 1982).

Fashion scholar Claudia Kidwell (1978) examined the dress of 18th century slaves through computer-assisted content analysis using newspaper advertisements for runaways as her dataset (Kidwell, 1978; Paoletti, 1982). Paoletti described some of the extensive fashion resources for research including advertisements, illustrations, magazines, and newspapers (Paoletti, 1982). Applying ML to Paoletti's use of content analysis for the study of historic costume adapts her model for the digital age.

In the field of CS, Matzen et al. (2017) created a framework for visual trend discovery by applying deep learning to identify re-occurring fashion attributes and used the attributes to label images (Matzen et al., 2017). In the study they analyzed fashion trends across millions of images to create style clusters that show visual similarities and trends among 44 international cities (Matzen et al., 2017). This study applied Matzen et al.'s (2017) framework for analyzing clothing and visualizing trends and used their dataset of clothing annotations, *Streetstyle-27k*, to understand fashion styles on social media. Matzen et. al. (2017) were one of the first to apply machine learning for large-scale visual trend discovery to understand geo-temporal fashion trends (Matzen et al., 2017).

Mechanisms of Fashion Change

Looking at the movement of a utilitarian accessory, such as the baseball-trucker hat, from casual wear to the luxury market offers an opportunity to critique and re-examine Economist Thorsten Veblen (1899) and Sociologist Georg Simmel's (1904) theories, now commonly referred to as "trickle-down theory" (Simmel, 1904; Veblen, 1899). In the "trickle-down" model, fashion change is perpetuated by the upper-class through a dialectical engagement between identification and differentiation (Simmel, 1904; Veblen, 1899).

Although wealth and social class were influential factors for fashion change, Simmel and Veblen's theory does not engage with other subject positions beyond class. Veblen describes "conspicuous consumption" in which the upper class created the model for consumption and all lower classes strived to imitate the upper class (Veblen, 1899). Simmel argued the cycle of fashion is perpetuated by the demarcation of class by the wealthy and imitation by the poor (Simmel, 1904). Similar to Anthropologist Edward Sapir's (1931) discussion of fashion and the ego, Simmel argued that fashion supplemented a person's lack of importance by individualizing their existence (Simmel,1904; Sapir, 1931). Simmel argued that the speed at which fashion changed correlated to the "nervousness" of the age in which people's desire to differentiate increased (Simmel, 1904, 8).

Sociologists Herbert Blumer (1969) and Fred Davis (1994) rejected the "trickle down" theory of fashion change and instead argued for a diffusion of styles based off the development of collective identities (Blumer, 1969; Davis, 1994). Blumer (1969) developed a theory of "collective selection" in which groups of people collectively choose styles to look "modern" as a means of coping with disorder and uncertainty about the future; therefore, fashion allowed individuals to collectively maintain control in response to rapid social change and upheaval (Blumer, 1969). Davis had a similar understanding of the diffusion of fashion styles; however, he attributed fashion change to ambivalence and ambiguities in identity formation when dress becomes a visual metaphor for the Western sense of self (Davis, 1994).

Simmel's correlation between societal instability and differentiation in dress is similar to Kroeber's (1919) earlier research, the foundation for his later work with Richardson, regarding driving factors in fashion change (Simmel, 1904). Kroeber (1919) took measurements of women's dresses from *Petit Courrier des Dames* and *Harper's Bazaar* from 1844-1919 to draw similarities between the rise and fall of civilizations to the curves and edges in material objects specifically garments (Kroeber, 1919). He argued that fashion change is not arbitrary and although fashion trends seem to change rapidly and without causality there is an order to the change similar to the order of civilizations (Kroeber, 1919, p. 259). Kroeber attributed fashion change to "civilizational determinism" rather than to the individual (Kroeber, 1919, p.261).

Understanding the seminal fashion theory contextualizes the movement of the baseball-trucker hat, utilitarian accessory, in every day wear and the luxury runway.

The baseball-trucker hat is a casual accessory designed to shade the face from the sun while playing baseball and absorb sweat. Fashion theory helps scholars explain why a hat can move between people and communities. Identifying the factors that motivate a group of individuals to collectively wear a baseball-hat beyond the baseball field invites the study of various fashion theories. Examining how scholars have analyzed fashion change in relation to socio-cultural events lays a framework for understanding the frequency of baseball-trucker hats in two social spaces.

CHAPTER 3

METHODS

The author employed descriptive and inferential statistics to analyze quantitative data acquired from the ML models. Quantitative research relies on numerical data and empirical inquiry to understand social phenomenon; the author used this method when applying ML to the documentation of a fashion trend (Frey, 2018). The research process began with empirical inquiry by the author and collaborative research with Computer Scientists (CS) to code a digital annotation tool and classifier for fashion trend recognition. Quantitative plots were used to illustrate analytics from the ML algorithmic computation. In the discussion section, the author interpreted social and historical trends, and the impact on luxury and mainstream fashion. Using a descriptive statistical approach, the author described and summarized the quantitative data in graphs, tables, and charts and included a commentary on emerging patterns and cultural significance (Coleman, 2018). The quantitative data extracted from the ML allowed for documentation and understanding trend frequency of baseball-trucker hats among two large image datasets from social media and luxury runways to inform classification for fashion trends and historical analysis.

Iterative Process

The research team met bi-weekly from August of 2018 to May of 2019 using an iterative design process to refine the ML software, build taxonomies, test the annotators, and label images to visualize the geo-temporality of the baseball-trucker hat among social media from 2013-2016 and luxury runways from 2000-2018. The author provided the research questions while the CS refined the Matzen et. al (2017) foundational algorithmic models for trend visualization and visual discovery using high-level concept recognition in ML to recognize objects in the datasets (Matzen et al., 2017). The collaborative work provided mutually beneficial data to understand the movement of fashion trends and inform refinement of the ML technology while documenting the frequency of baseball-trucker hats. The ML quantified the rates of change through analyzing images.

Using descriptive statistics, this research team mapped the geo-temporality of baseball-trucker hats, as they appeared in social media posts from 2013-2016 and international runways (full list of designers listed in appendix) from 2000-2018. The CS collaborators created the datasets by populating images from Instagram and *Vogue Runway* to feed to the annotator tool for labeling. In the first annotation tool images were non-labeled, meaning they did not have associated tags telling the computer the subject of the image. The goal of this annotator was to allow the author and CS to manually train the data through the tool and label upper body images as "having hats," "no hats", or "baseball-trucker hats." Once the author and CS labeled the initial training dataset the CS fed the images to the classifier to establish the parameters for identifying a baseball-trucker hat. After the classifier labeled a series of images the second annotation tool validated the classifiers results and checked for accuracy (See Figure 3.1 for process).

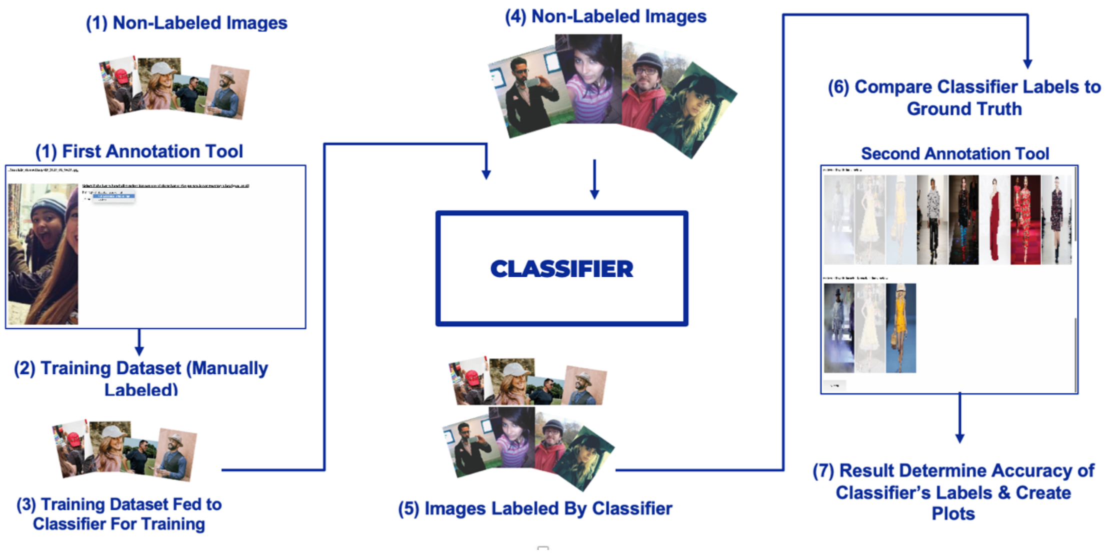

Figure 3.1: Step-by-step Iterative Process for Annotating and Classifying Images

Vogue Runway Dataset

The author chose the *Vogue Runway* archive from Vogue.com to populate the luxury market dataset (see figure 3.2 below). The dataset included approximately 576,907 runway images from the year 2000 to 2018. The *Vogue Runway* is an open access digital archive indexing designer runway shows from global fashion weeks. Vogue.com organizes the runway shows by season and designer with each collection look listed in a digital slideshow. The archive begins in 1989, although the runway coverage significantly increased around the early aughts with the ubiquity of digital photography. According to the *Business of Fashion* (2019) *Vogue* initially listed runway shows only reviewed by *Vogue* journalists; however, in 2019 Vogue began offering a subscription model to allow brands, upon editorial approval, to pay upwards of $20,000 per year for index inclusion of images but without journalist coverage (Fernandez, 2019). Since the pay-for-coverage model began the reported collections included on Vogue.com increased from 445 to 480 in Spring of 2019 (Fernandez, 2019).

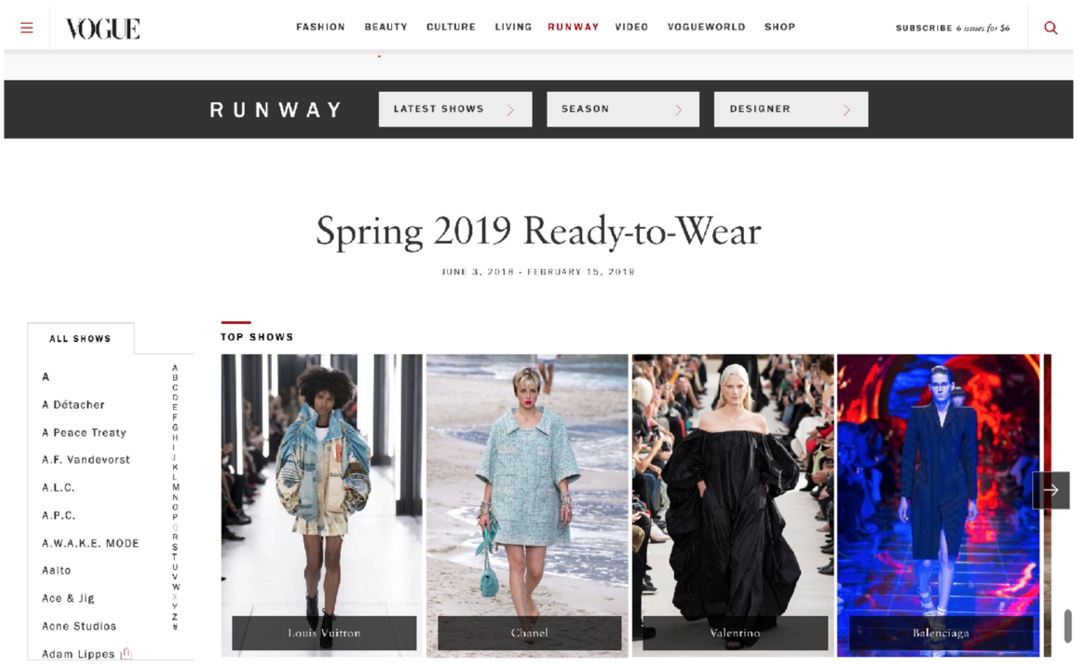

Figure 3.2: *Vogue* Runway Designer Database Screenshot. Retrieved from www.vogue.com/fashion-shows.

Instagram Dataset

The second dataset chosen to represent images on social media and everyday wear was populated from the *Streetsyle27-k*, an annotated dataset of 27,000 images acquired from the social media photo sharing platform Instagram (see figure 3.3 below). The dataset created by Matzen et al. (2017) contains clothing attribute tags and geolocation and timestamps from June 2013 to June 2016 for 27,000 images with label annotations from the original 100 million photographs sampled (Matzen et al., 2017). The cities sampled in the data were based upon the geolocation tags already in the dataset of USA cities including Austin, Chicago, Los Angeles, New York City, and Seattle. Each city had 100,000 images with a total of 500,000 images for all five cities. The dataset was limited to 2013-2016 due to changes in Instagram's legal policy. After 2016 Instagram only made public user data available through purchase.

Figure 3.3: *Streetstyle-27K* an Annotated Dataset of 27,000 images from Instagram. Retrieved from Matzen et al., 2017.

First Annotation Tool

The first annotation tool presented individual images of upper bodies to distinguish the category of hats worn by individuals in each image (see figure 3.4 below). The purpose of the first annotation tool was to manually label images and distinguish between visored and un-visored hats to help the computer understand what type of shapes to recognize. The computer analyzed the labels created by the author and CS from the annotation tool in order to detect similar shapes when presented with additional non-labeled images. CS aggregated non-labelled images from *StreetStyle-27k*, image sharing site Flickr, and Google Image of the upper body to feed to the annotator for labeling. The author and CS labeled approximately 1000 images through the tool by selecting the label from a drop-down menu presenting the options "baseball-trucker hat," "not baseball-trucker hat," or "no hat." This process gave the foundational "training data" to the computer to identify the qualities of a hat, baseball-trucker hat, and no hat.

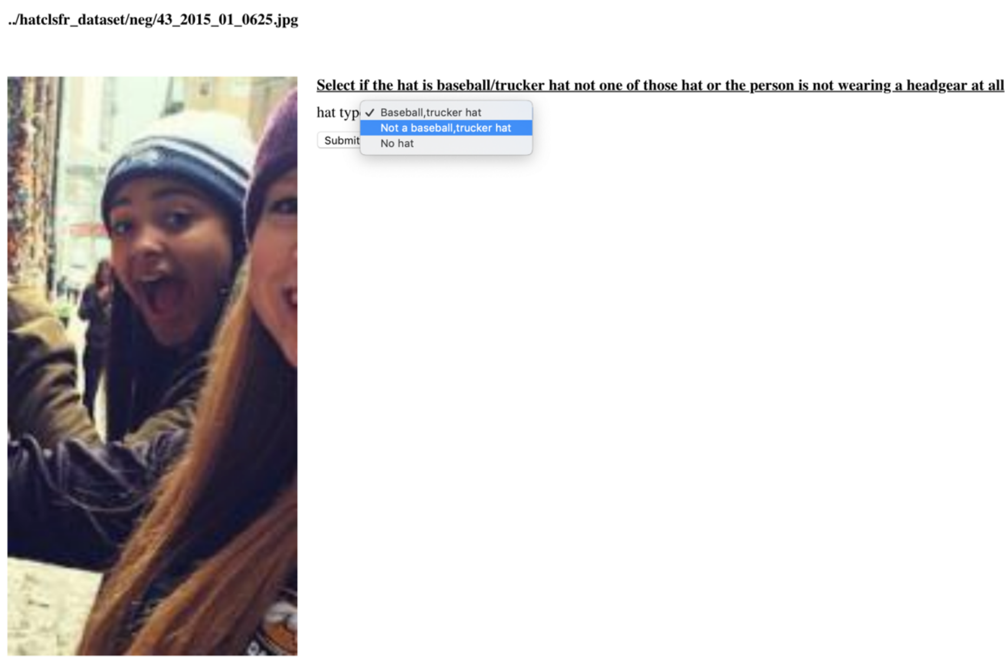

Figure 3.4: First Iteration of Annotation Tool

Second Annotation Tool

The interface for the second iteration of the annotation tool evolved to include eight images instead of one allowing for efficient labeling of multiple images (see figure 3.5 below). Instead of a single image the second annotation tool presented eight images with full body runway looks populated from the *Vogue Runway* dataset. The second iteration of annotation occurred to collect a "ground truth" in testing the accuracy of the training data's classification (i.e. whether or not the classified images were accurate) for the *Vogue Runway* dataset. Understanding the "ground truth" is critical to evaluate the accuracy of the resulting plots. The author and CS selected the images with hats by clicking on each image creating a visible filter which lowered the image saturation. The selected images of hats from the top row appeared below the top images prompting the author to click images with baseball-trucker hats. The author and CS labeled approximately 1,720 images in the first iteration.

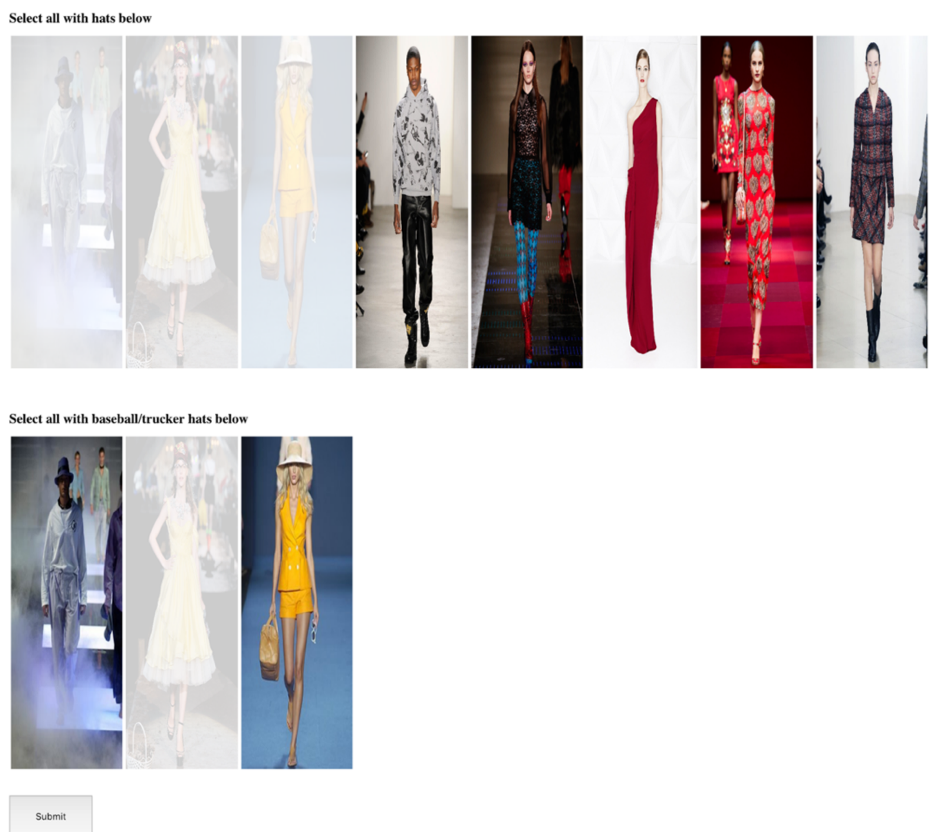

Figure 3.5: Second Iteration of the Annotation Tool Screenshot.

Ongoing Refinement and Validation

After the running images through the first iteration of the classifier several misclassifications were identified and the rate of accuracy for the *Vogue Runway* images was below average. The classifier performed poorly on the *Vogue Runway* dataset; however, the classifier calibrated for images similar to the training set which included Instagram images from *Streetstyle-27k*, and Google search images. The difference in the images populated from the *Streetstyle-27k* and Google images versus those appearing in the *Vogue Runway* potentially created the difference in classifier performance. Since the training dataset had one orientation (i.e. front facing and traditional visor shape) the images that appeared on the runway were sometimes tilted or hybrid styles causing them to be misclassified or inaccurately labeled. The CS researchers found mis-labeled images (see figure 3.6 below) due to variations in hat orientation or the presence of hybrid hats containing certain characteristics of baseball-trucker hats but not all. The figure below shows eight types of hats that the tool misclassified due to differences from the initial training dataset. The classification of hybrid styles were not taken into consideration during the initial training process nor were images of hats where the visor bill is hard to identify. The consideration of changing hybrid styles is a topic outlined for further research.

Figure 3.6: Variety of Hats Populated from *Vogue* Runway Dataset that the Classifier Often Mislabeled Due to Differences from Training Dataset

Modifications and Adjustments

In order to address the recognition issues, the CS team re-trained the classifier with images similar to the misclassified images. By labeling images with additional orientations and hybrid styles the ML tool recognized variations from the standard hat images. The CS researchers also looked at the images classified and misclassified by the current iteration of the classification tool from the runway images, re-labeled them, and retrained the classifier with the newly labeled images.

Second Iteration

The CS initiated a second iteration of the annotation and classification process (see Figure 3.7 below). In order to refine the classifier, the CS fed non-labeled images into the current classifier and isolated the images only labeled as having hats. Once those images were isolated they were re-fed into the annotation tool and labeled by researchers in order to retrain the classifier. Once the classifier was retrained to recognize hybrid hat styles and alternate orientations it re-labeled the *Vogue Runway* dataset and created the quantitative plots results.

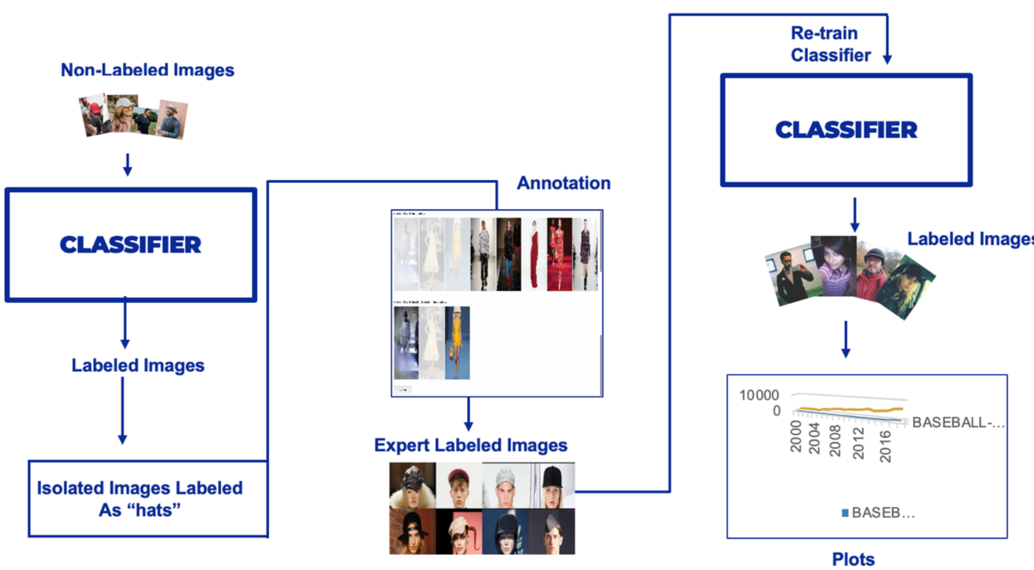

Figure 3.7: Second Iteration to Refine and Retrain Classifier Tool

CHAPTER 4

RESULTS

The ML annotators and classifiers identified images and categorized results into visual plots with high rates of accuracy. The plots reflected the frequency of baseball-trucker hats compared to other hat styles on the luxury runway from 2000-2018 in the *Vogue Runway* dataset and the social media posts from 2013-2016 in the *Instagram* dataset. Below are the plots showing the frequency of baseball-trucker hats in the five US cities surveyed compared to other hats in the *Instagram* dataset followed by the frequency of baseball-trucker hats separated by city. The dataset for the plots includes the *Instagram* dataset quantifying the frequency of baseball-trucker hats in Austin, Chicago, Los Angeles, New York City, and Seattle. The author only surveyed United States cities among social media images to narrow the scope of the study while the five cities surveyed were the only US cities documented in the *Instagram* dataset from Matzen et al. (2017). The last plot shows the frequency of baseball-trucker hats compared to other styles of hats from 2000-2018 in the *Vogue Runway* dataset.

Rates of Accuracy

The confusion matrixes in the tables below show the rates of accuracy for the classifier among the social media dataset from Instagram and the luxury runway dataset from the *Vogue Runway.* The social media had an overall accuracy rate of 92.18% while the *Vogue Runway* dataset had an overall accuracy rate of 97.96%.

Confusion Matrix

Each row is one category in true data (i.e. the label that the human researcher gave to the image) and each column represents classifier's response. The green boxes represent the rates of accuracy while the red boxed represent the inaccuracies. The percentages in the green boxes should be high since those represent the rate at which the manual research label matches the label of the classifier.

Social Media Overall Rate of Accuracy = 92.18%

	Classified as No Hats	Classified as Other Hats	Classified as Baseball-Trucker
True No Hats	96.385542	3.614458	0
True Other Hats	1.709402	88.888889	9.401709
True Baseball-Trucker Hats	0	8.943089	91.056911

Table 4.1: Social Media Confusion Matrix Showing Rates of Accuracy

***Vogue Runway* Overall Rate of Accuracy = 87.96%**

	Classified as No Hats	Classified as Other Hats	Classified as Baseball-Trucker
True No Hats	93.842365	6.157635	0
True Other Hats	3.282828	87.878788	8.838384
True Baseball-Trucker Hats	0.49505	17.326733	82.178218

Table 4.2: *Vogue Runway* Dataset Confusion Matrix Showing Rates of Accuracy

Plots

Percentage of Baseball Trucker Hats in All US Cities on Social Media from 2013-2016

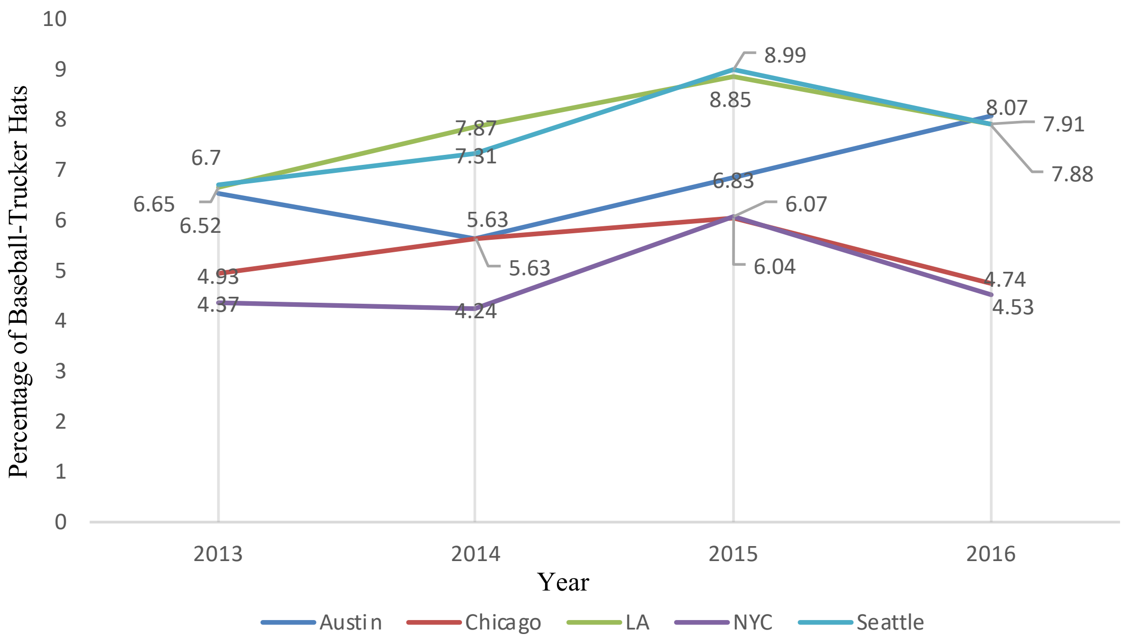

Figure 4.1: Percentage of Baseball-Trucker Hats on Social Media by City and Year

The line graph above shows the percentage of baseball-trucker hats on social media by year and city. The Y-axis represents the percentage while the X-axis represents the year and each colored line represents a city. The overall frequency of baseball-trucker hats among all images of hats on the Instagram dataset was low from 4.37%-6.67% and the annual fluctuations followed similar patterns in all five cities. The lowest percentage of baseball-trucker hats among all images of hats was in New York City and the highest percentage of baseball-trucker hats was in Los Angeles.

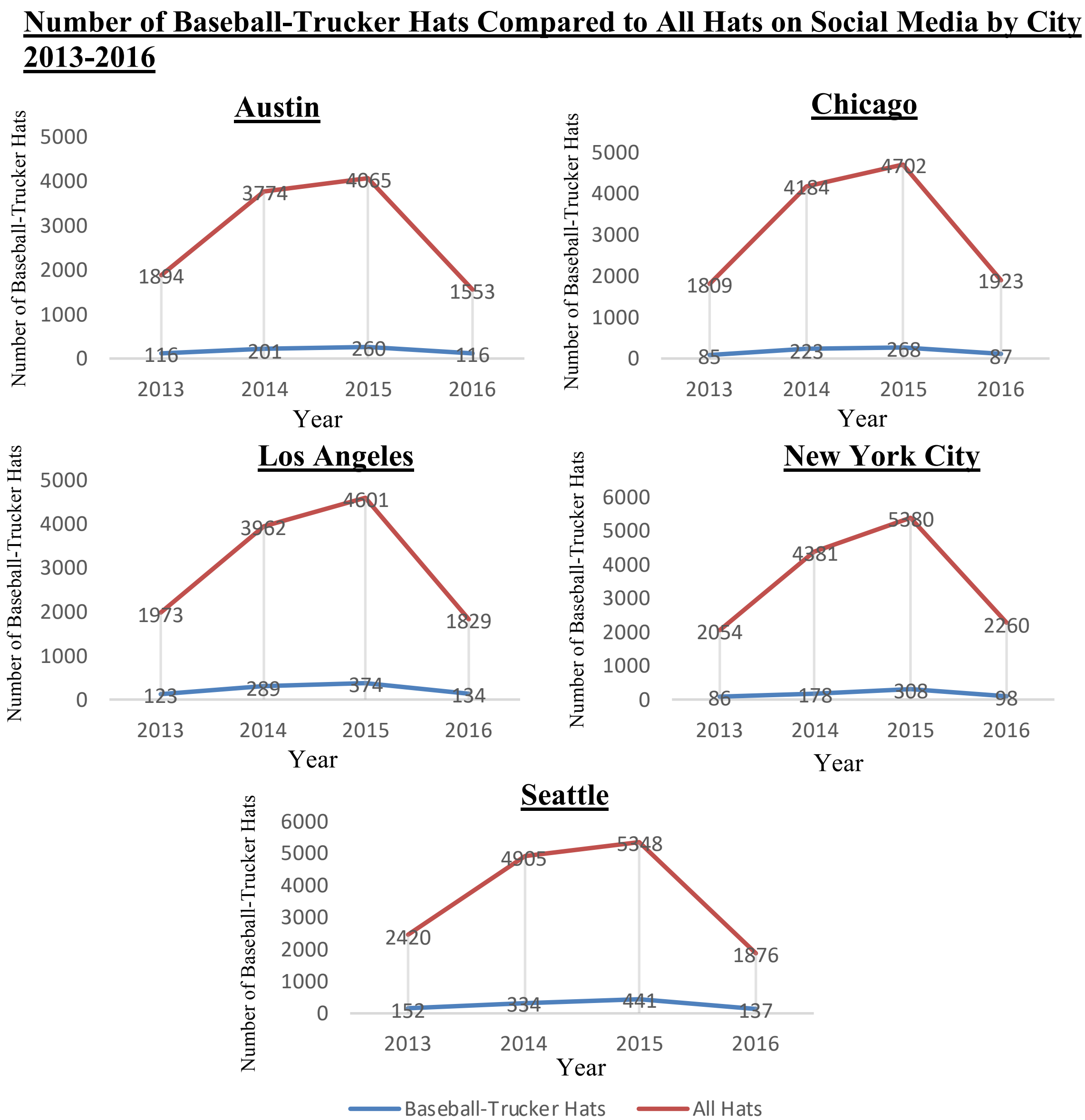

Figure 4.2: Number of Baseball-Trucker Hats in Austin, Chicago, LA, NYC, and Seattle from 2013-2016

Figure 4.2 shows the number of baseball-trucker hats in the US cities surveyed by year from 2013-2016. The Y-axis represents the number of hats, the X-axis represents the year. The frequency of baseball-trucker hats among all images of hats was low although the annual fluctuation was similar among all cities surveyed. Seattle had the most baseball-trucker hats from 2013-2016 with 1,064 appearing on the social media dataset followed by Los Angeles with 920, Chicago with 920, Austin with 693, and New York City with 647.

Number of Baseball-Trucker Hats on the Vogue Runway Compared to All Hat Styles from 2000-2018

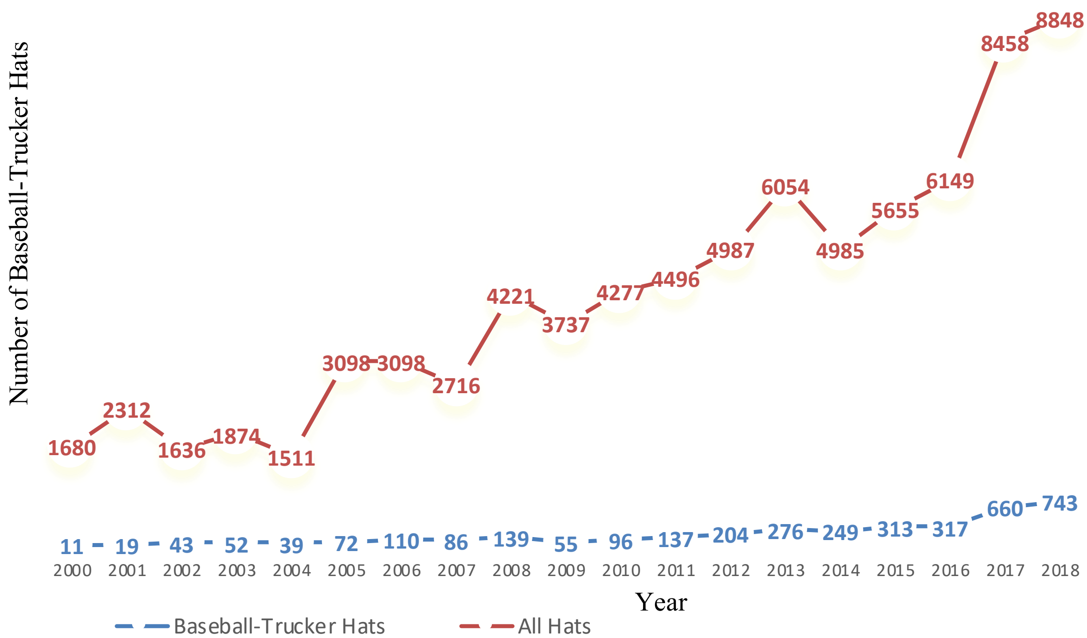

Figure 4.3: Number of Baseball-Trucker Hats Compared to All Hat Styles in the *Vogue Runway* Dataset from 2000-2018.

The final plot, figure 4.3, is the second iteration of the classifier results which shows the number of baseball-trucker hats compared to all hat styles in the *Vogue Runway* dataset from 2000-2018. From 2000-2008 baseball-trucker hats appeared on the runway although they did not dramatically increase annually. From 2009 to 2018 there was a slow but steady annual increase of baseball-trucker hats. There with a large spike from 2016 to 2017 where baseball-trucker hats doubled from 317 to 660 total hats. The number of total hats on the runway annually increased although the increase was not continuous. The baseball-trucker hats were a small percentage of total hats on the runway but were present every year from 2000-2018.

CHAPTER 5

DISCUSSION

The plots show a low frequency of baseball-trucker hats with similar annual fluctuations by city on social media and a rise in baseball trucker hats from 2008 to 2018 with a spike in 2016 to 2017 on the luxury runway. According to the plots of the Instagram images the frequency of baseball-trucker hats remained fairly constant during the four-year period from 2013-2016 although the frequency of the hats on the luxury runway started to annually increase around 2008 through 2018 with a spike in 2016 to 2017. Several cultural factors could have increased the popularity of the hats and contributed to their appearance on the luxury market. The economic crash in 2008 could have led to a rise in casual and understated styles; furthermore, the rise of the luxury baseball-trucker hat may fit under the stylistic trends of *Normcore* and *Athleisure,* and streetstyle. The popularization of the "Make America Great Again" (MAGA) baseball hat worn by Donald Trump in his 2016 presidential campaign also potentially contributed to the popularity of baseball caps (Parker, 2017).

Global Economic Crash

The global economic crash started in 2008, the largest recession since the 1930s, had global repercussion extending into all markets including the fashion industry (Solman, 2018; Cassidy, 2018). Millions of Americans lost their homes, jobs, and retirement savings (Cassidy, 2018). Following the collapse, fashion buyers placed smaller orders with fears that customers would shop conservatively during the recession (Wilson, 2008; Cartner-Morley, 2008). The *Vogue Runway* dataset shows a steady rise in baseball-trucker hats in 2008 rising each year until 2018. The increase of a functional accessory could signify a possible shift in luxury fashion towards utility as the global economy declined. Even if a customer was able to afford a luxury item during the financial crisis, wearing fine garments and luxurious goods might be less appealing during a time when the majority of Americans were struggling to pay bills and recover their homes. Wealthy Americans might want to dress inconspicuously, blend in, or not draw attention to their privilege. More affordable accessories might be more appealing to customers no longer able to afford higher priced items but wanting to turn to fashion as a form of escape or recreation.

The *Instagram* dataset plots show a steady frequency of baseball-trucker hats compared to all hats styles in the US cities surveyed in the study, although, the same frequency is not present on the *Vogue Runway* dataset. Of the cities surveyed Austin, Texas was the only city with a slight increase in baseball-trucker hats from 2015 to 2016, a time when GOP presidential candidate Donald Trump wore a "Make America Great Again" hat to campaign rallies, perhaps representative of the state's conservative political leanings. Los Angeles, New York City, Seattle, and Chicago had minor decreases in baseball-trucker hat frequency from 2015 to 2016 and minor increases each year from 2013 to 2015 followed by a minor drop in 2016.

Normcore, Athleisure, and Streetwear

The rise of baseball-trucker hats in the luxury market is not surprising considering several cultural trends including *Normcore, Athleisure*, the popularity of streetstyle, and dressing ironically. There is scant documentation of *Normcore* among academic scholarship; however, the artist collective K-hole, as well as, several popular press publications including *Vogue* and the *New York Times* have documented the trend (Youth Mode, 2013; "Normcore," 2018; Williams, 2017). *Normcore* is a portmanteau, a combination of the words "normal" and "hardcore", according to *Vogue* (2018) a term used to describe a style of ironic non-descript aesthetic that signifies the intent to appear normal ("Normcore," 2018). *Vogue* attributed the phrase *Normcore* to art-collective and forecasting group K-hole's 2013 trend report titled *Youth Mode: A Report on Freedom*. ("Normcore," 2018; Youth Mode, 2013) K-hole describes *Normcore* as a "post-authenticity coolness that opts into sameness" which "capitalizes on the possibility of misinterpretation as an opportunity for connection — not as a threat to authenticity" (Youth Mode, 2013, 28). *Normcore* is about wearing off brand items to appear ironically bland, a deliberate decision embracing the anti-trend. The baseball-trucker hats fit into the normcore uniform of supportive sneakers, plain t-shirts, and simple inconspicuous garments.

The inconspicuous displays of wealth through sportswear and leisure clothing, associated with *Normcore*, aligns with the style of technology giants Jeff Bezos of Amazon, Bill Gates of Microsoft, and Mark Zuckerberg of Facebook: some of the richest men in the world according to *Forbes Magazine* (Kroll and Dolan, 2019). Could the rising wealthy class of tech giants influence the popularity of inconspicuous clothing and changing trends towards luxury sportswear or are there other socio-cultural events during the late aughts influencing the shifting styles? Perhaps with a growing wealth discrepancy there is a desire to hide wealth and consume inconspicuously or perhaps the wealthiest people in the world of the tech industry are less occupied with dress and appearance? Mark Zuckerberg and Steve Jobs famously wore uniforms of jeans and t-shirt perhaps to minimize efforts in appearance or because of a lack of interest in self-fashioning.

Athleisure, a compound of "athletic" and "leisure," is a recent clothing category dominating the market since the 2010s consisting of casual sweats, yoga compression pants, as well as, other athletic garments worn outside of the gym or outdoor recreational locales (Green, 2017, Thompson, 2018). *Athleisure* has shifted from a trend category to a lifestyle of "wellness" and leisurewear is possibly tied to the rise of the gig economy consisting of independent contractors and freelancing (Salfino, 2017). Baseball-trucker caps, moving from a sports uniform to a leisure staple, compliments the *Athleisure* aesthetic.

Morgan Stanley expects the *Athleisure* and "activewear" market to grow to $83 billion by 2020 from its current estimate at $44 billion and rising (Wilson, C., 2018; "The Athleisure Trend is Here to Stay," 2016) Luxury brands infiltrated the activewear market, as brands like Givenchy, Off-White, and Gucci have designed casual sportwear (Wilson, C., 2018). Sportswear brand Adidas collaborated with a plethora of luxury designers including Stella McCartney, Raf Simmons, Yohji Yamamoto for Y-3, Kanye West for Yeezy, Rick Owens, and Ricardo Tisci (Johnson, 2014). Nike also thrives on luxury designer collaborations which have included Louis Vuitton's creative director Virgil Abloh, Commes des Garcons creator Rei Kawakubo, Dior's creative director Kim Jones, and Balmain's Olivier Roustieng (Wolf, 2018).

Although the dominance of *Athleisure* in the fashion industry seemed sudden, the shift in casual American dress codes has been gradual. Although fashion scholars have not officially applied the term *Athleisure,* Fashion Historians Elizabeth Wilson (2003), Jennifer Craik (2005), and Diedra Clemente (2014) are among the scholars who have chronicled the slow integration of sportswear, leisure, and recreation into everyday dress (Wilson, 2003; Craik, 2005; Clemente, 2014). Wilson (2003) discussed the changing women's fashion silhouette in the 20th century as sports became elevated and women desired athletic physiques and active lifestyles (Wilson, 2003). Craik (2005) attributes the rise in athletic wear to several factors including the development of advanced synthetic fabrics like nylon, Lyrca®, and acrylics, industrialization, political shifts like the rising women's movement, and shifting concepts of modernity and progress (Craik, 2005). She also acknowledged the mix of streetwear and sportswear among American basketball players and hip-hop especially through Nike and Michael Jordan's collaborative Air Jordan shoes (Craik, 2005). She noted the adoption of Nike sportswear by the club and raver scene of the 1990s (Craik, 2005). Craik (2005) discussed the 20th century rise of looser-fitting clothing, desire for functionality and comfort, sports-inspired casual clothes including increase in baseball caps (Craik, 2005).

Clemente (2014) chronicled the rise of sportswear and contemporary casual dress codes through the influence of leisure in American collegiate dress from the mid 20th century to the present (Clemente, 2014). She attributed the modern American "casual" wardrobe to trends popularized on college campuses rooted in utilitarianism and comfort, blurring lines of class and democratizing clothing by removing visible markers of demarcation (Clemente, 2014). Clemente credited the widespread adoption of a new "casual" attire and shifting dress codes to American college students especially the middle-class men, often less regulated than their female counterparts, who were able to push the boundaries of appropriate collegiate dress (Clemente, 2014). Whether beginning with the integration of women into sports and recreation, industrialization and technological advances in textiles, or a rising casual aesthetic popularized on college campuses culminating in a multi-billion-dollar market, athletic wear has evolved over the past hundred years in American history.

From Luxury to Ideological Team and "Imagined Communities"

Anthropologist William Kelly (2018) and Fashion Historian Jennifer Craik (2005) examined the shift of sports clothing from athletics to everyday wear through the history of sportswear and American clothing. (Kelly, 2018; Craik, 2005). Craik argued that sports clothing has been integral to youth identification back to the 1950s attributing the rise of sportswear to the development of synthetic fabrics (e.g. Lycra®, nylon) (Craik, 2005). She credited Prada for popularizing nylon in the 1990s in luxury fashion (Craik, 2005; Handley, 1999).

Headwear was historically a visible marker for social class distinction in the United States and Britain, although the baseball cap was a transitional accessory that blurred the class divide when professional coaches began wearing team hats in lieu of top hats (Kelly, 2018; Crane, 2000). Perhaps the frequency of an arguably lower-class item on a luxury runway documents the blurring of class distinctions and changes in luxury fashion. The shift arguably signifies a new luxury market offering more accessible items to young "fans" of the brand. Craik (2005) argued that sports uniforms including caps influenced a growing leisure aesthetics (Craik 2005). Baseball-trucker hats are more financially accessible, durable, and can withstand more wear than garments. Hats are often less likely to be purchased through second-hand retailers thus increasing direct sales with a brand. The branded hats provide a form of advertising, acting as a walking billboard for brands while customers align their identities with the brand's aesthetic.

The baseball cap increased in frequently through a series of cultural shifts and branding decisions beginning with the rise of Little League baseball in 1950s and the distribution of free branded caps in the 1970s (Kelly, 2018). The hat transitioned from professional sportswear to everyday wear during the popularization of Little League baseball in the 1950s when kids and their parents began wearing caps to support their teams (Kelly, 2018). By the 1970s corporations and institutions, like John Deere and Budweiser, distributed free caps with plastic adjustable straps as an opportunity for marketing and visibility and people started to wear the free branded hats as they were utilitarian and convenient (Liliefors, 2009; Kelly, 2018). Kelly argued that wearing the hat created a sense of performativity to exist within an "imagined community" and that wearing the baseball hat in the context of a game or otherwise shows a sense of support (Kelly, 2018, 272). He discussed the hats' crossover beyond sports games and into everyday life, identifying the influence of the hip-hop community starting in the South Bronx in the early 1970s (Kelly, 2018). The baseball hat has now entered luxury fashion and is an ideal medium to display messaging and show luxury brand allegiance for young "fans," moving a long way from the baseball field.

Kelly's (2018) analysis of hat adoption in everyday wear as an allegiance to an "imagined community" can be applied to the luxury market in examining brand allegiance and affiliation (Kelly, 2018). Whether through Gucci or Balenciaga, an individual can signal their allegiance to a particular brand that represents their style. Most luxury brands make their greatest profits from the sale of accessories like handbags, shoes, and beauty products (Chung, 2017; Bain 2017). Fashion consultancy firms Exame BNP Paribas and VR Fashion Luxury Expertise reported in 2017 that luxury clothing is a "brand-defining core category," but is not profitable (Conti, 2017). Luxury brands lose money on their clothing, especially when few customers will purchase items at full price (Bain, 2017). Guram Gvasalia, CEO of Vetements and creative director of Balenciaga, ended Vetements runway shows in 2017 and told *Women's Wear Daily (2017),* that "today shows have nothing to do with clothes anymore, most of the looks are not even produced and never get to the shop floor. Shows are there merely to sell a dream that at the end of the day will sell a perfume or a wallet in a duty-free store" ("Amid Runway Overload," 2017). Previous CEO of Calvin Klein, Tom Murray discussed Calvin Klein's business model with *Business of Fashion's* Imran Amed (2011) and emphasized the value of ready-to-wear clothing to create an aura for the brand despite being unprofitable and therefore more of a marketing expense (Amed, 2011). For many luxury brands, relying on the profits of clothing is unreliable and often a liability.

Several luxury brands, including Louis Vuitton and Balenciaga, have recently hired young creative directors known for a casual streetstyle aesthetic. *Ad Week* (2018) reported on Instagram's influence on the rise of streetstyle in luxury fashion as brands have begun to tap into Instagram trends (Sulima, 2018). Louis Vuitton appointed Virgil Abloh, founder of Off-White and friend of rapper Kanye West, as their creative director in 2018 (Friedman and Paton, 2018). Balenciaga recently appointed Guram

Gvasalia; both designers are contributing to a changing concept of luxury (Sulima, 2018). According to *Business Insider* (2017) streetwear has boosted global luxury sales and luxury's customer base is likewise changing, from an older to a younger generation (Barry, 2017). A 2017 study from Bain & Company estimated that high-end street wear helped boost global sales by 5% to $309 billion in 2017 and brands are investing more in Instagram marketing and influencers (Barry, 2017). The report documented a $2.5 million market for luxury t-shirts and half a billion market for sneakers, unusual for the luxury market (Barry, 2017).

Producing more affordable products like hats or shoes give young "fans" an opportunity to support their favorite brand. Instagram and streetstyle potentially influenced that changing luxury market that caters to Millennials and Gen Z'ers. Mckinsey & Company defined Millennials as individuals born between mid-1980s to 2000s and Gen Z as those born between the year 1995 to 2010 (Frances and Hoefel, n.d.) Millenials and Gen Z'ers might not be able to afford the clothing with thousand-dollar price tags but are able to save for $300 or $700 items (Frances and Hoefel, n.d.). *Forbes* (2018) reported on the rising spending power of Millennial shoppers, while the CEO of Kering, Francois-Henri Pinault said Millennials and Gen Z'ers account for almost 50% of Gucci's net sales (Primo, 2018). Gucci's recent collection of baseball and trucker caps, sneakers, and re-issue of the logo T-shirt offer young consumers relatively lower priced items that can be worn every day. Producing ready-to-wear accessories catering to Millennial representation is key to satisfying the customer base. Deloitte (2017) reported that Millennials are less interested in the previous generations outward displays of wealth and strive for authenticity and ethical production ("Bling it On", 2017).

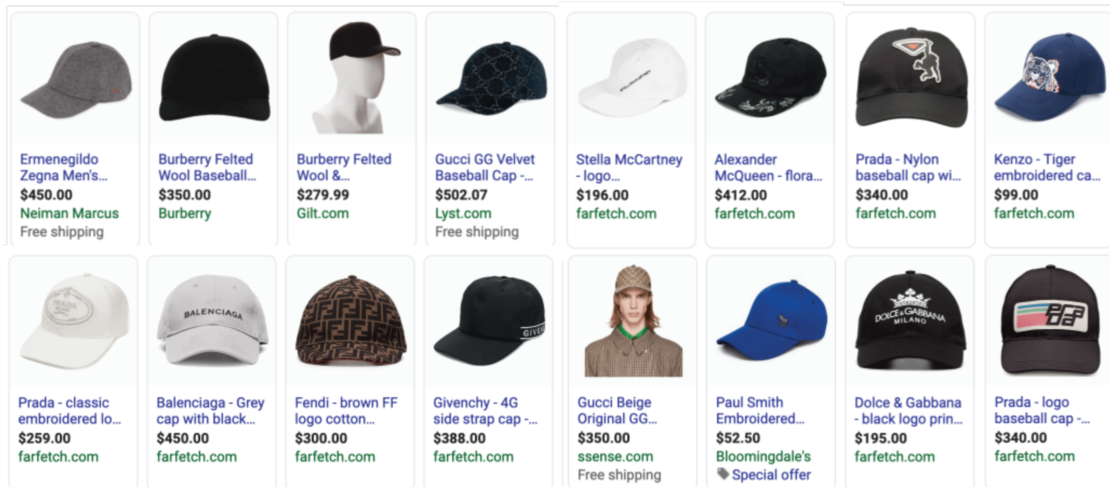

Figure 5.1: Selection of Luxury Baseball- Trucker Hats Available on E-commerce in March 2019. Retrieved from Google Shopping in March 2019.

Alessandro Michele, creative director of Gucci, was the first to officially bridge the sports merchandise and luxury fashion through a 2018 collaboration with the Major League Baseball (MLB) but not the first to collaborate with MLB and push the boundaries of sports licensing (Bobb, 2017; Kelly, 2018). The Pre-Fall 2018 collection marked MLB's first collaboration with a luxury brand featuring a series of Gucci baseball hats with the NY Yankee insignia (see figure 5.3) paired with silk embroidered gowns, embracing the juxtaposition of luxury tailored garments and causal sportwear (Bobb, 2017; Fischer 2017; Estiler 2018) Although Gucci was the first luxury brand to adopt the Yankees logo, director Spike Lee was the first celebrity granted a special exception to the Yankee licensing code when he was issued a red Yankees hat outside of the team colors (Kelly, 2018). In 1996 Lee requested the red hat instead of the traditional navy to match his red Yankees jacket (see figure 5.4 below) and wore the hat to the 1996 World Series sparking a change in sports licensing (Kelly, 2018; Patterson, 2015). In 2016 New Era re-issued the red Yankees hat through a collaborative collection with Lee titled “1996,” offering four styles inspired by the original 1996 red hat (Cardiner, 2014). When Gucci released the MLB collaboration, Lee wore a full Gucci ensemble including his classic red Yankees cap to the 75th Venice Film Festival.

Politics and the “MAGA” Hat

Another simultaneous baseball hat phenomenon occurred on the 2016 U.S. presidential campaign trail when Republican nominee Donald Trump wore a red visored hat with white embroidered lettering “Make America Great Again” (Kelly, 2018). The hat has become known by its acronym and called the MAGA hat (Kelly, 2018). Appealing to working-class America, Trump wore and distributed MAGA hats at explosive rallies and charged public engagements while several media outlets reported on the hat’s emblematic symbol MAGA as suggestive of racism and bigotry (Bailey, 2019). The phrase “Make America Great Again” was a slogan Trump adopted from President Ronald Reagan and the iconic red hat became a symbol of American pride while also signifying the wearer’s affiliation with President Trump’s bigoted policies and statements (Abcarian, 2019; Givhan, 2019). The hats have incited violence as many people wearing the hats have attacked others or been victims of attack (Parker, n.d). Millennials have ironically co-opted the style according to the *New York Times* (2015) in trendy neighborhoods like Brooklyn or Silverlake replacing the MAGA slogan with humorous phrases (Parker, 2017).

Rapper and fashion designer Kanye West supported Trump through a series of tweets on the social media site Twitter, wore a slightly stylized MAGA hat on visits to the oval office, during concerts, and on *Saturday Night Live* causing controversy among the hip-hop, rap, and liberal Hollywood communities (Haas, 2019; Placido, 2018). Whether inciting patriotism, hope, violence, irony, or humor, the iconic MAGA hat has likely contributed to the popularization and increasing trend of visored caps.

In some ways the appearance of the baseball-trucker hat, an object meant to absorb sweat and resist stains, specifically designed for the street, the field, or sun, is antithetical to the concept of luxury and runway. However, the hat's appearance as a luxury item can be justified considering the fallout of the financial crisis and shifts towards casual dress codes promoting leisure and recreation. The influence of streetstyle and casual clothing paved the way for the adoption of the baseball hat among historically formal spaces like the fashion runway.

Figure 5.2: Donald Trump (left) Wearing a *MAGA* Hat During His 2016 Campaign Photographed by Gage Skidmore. Used Creative Commons. (right) Protestor at 2017 San Francisco Pride Parade wearing "Make America Gay Again" hat photograph by Pax Ahisma Gethen. Used Under Creative Commons.

CHAPTER 6

CONCLUSION

Summary of Results

Social scientists including Richardson (1940) and Kroeber (1940), Jack (1948) and Schiffer (1948), Lowe (1982) and Lowe (1982) have systematically attempted to quantify fashion change in relation to cultural phenomenon. ML provides a new opportunity to explore extremely large image datasets (Richardson and Kroeber, 1940; Jack and Schiffer, 1948; Lowe and Lowe, 1982). Combined with socio-cultural interpretation of trends, fashion studies scholars will be able to explore new theories, document fashion history, and provide trend analysis of the data presented through ML. Matzen et al. (2017) developed the framework and software for visual trend discovery which laid the foundation for the research and provided the tools and technology to recognize patterns among the large image datasets (Matzen et al., 2017). This study applied ML for pattern recognition through interdisciplinary research conducted between Computer Scientists and Fashion Scholars showing a rise in baseball-trucker hats on the luxury runway not previously seen before 2008. This rise in causal sports caps on the luxury market aligned with several popular streetstyle trends, the 2016 presidential campaign, among other economic and social influences.

ML is not able to currently predict trends; however, it quantifies and documents the frequency of past trends, making it a useful tool to study patterns in culture through aesthetics. The resulting data relies on scholarly interpretation and will enrich socio-cultural analysis in fashion theory. Although ML algorithms offer valuable information they are not currently predictive or conclusive without a human analyst to synthesize the data and form conclusions.

Limitations

Computer Literacy. There was a learning curve for understanding key Computer Science concepts which was initially challenging. The communication across disciplines challenged the researchers as the CS team spent time explaining the tools and other basic CS principles to the author.

Fashion Object Selection. There were limitations to the fashion object selection due to limitations of the ML tool in analyzing full body images. Most of the images in the *Instagram* dataset were upper body images making an accessory on the upper body appear more frequently and thus a better selection.

Access to Data. Access to images for the dataset was a challenge considering Instagram's changes to legal policies limiting access to user information and narrowing the dataset. Lack of social media sites in the early aughts limited digital documentation and social media datasets.

Ongoing Refinement. Another limitation of the study and collaboration was the continual refinement and ongoing changes to the classifier tool thereby changing the plot results. There were ongoing changes to the classifier tool, therefore changing plot and dependence on changing and evolving results proved to be challenging.

Rise in Microtrends. The rise in microtrends and high frequency in small simultaneous trends and diffusion of styles potentially caused lack of data. Since baseball-trucker hats were potentially a niche trend finding a large distribution among the dataset was potentially challenging compared to examining a more general silhouette trend.

Inherent Bias of Datasets. It is important to consider the purpose of the datasets when analyzing the results. Instagram is a curated collection where individuals often post their best images while a baseball-trucker hat often casts a shadow over the face in a photograph. The *Vogue Runway* images documented collections created to sell merchandise and promote the fantasy and aura of a brand. Considering the purpose of the dataset is important to understanding context.

Future Work

Visualizing Hybrid Styles and New Categories. Further examining the hybrid hat style and new categories of hats that the classifier identified through its misclassification on the *Vogue Runway* including a riding cap/baseball cap crossover would be valuable for future research. By measuring the height of the front panel, changing shapes of brims whether flat or curved could contribute to the visualization of changing silhouettes of hats over time. Measuring the differences in shape and styles can be used to visualize the emergence of new hat styles and consider the evolution of styles.

Tracking Additional Fashion Objects. Applying the methodology to trace the geo-temporality of similar objects with historical documentation of movement to the luxury market such as denim, t-shirts, and sneakers could be beneficial for future work. By connecting the movement of similar objects wider conclusions can be drawn in understanding the changing class distinction and changing conceptualization of the luxury market.

Extending the Dataset. Extending the dataset to include fashion plates or advertisements would allow for research over a longer historical timeline perhaps investigating changing styles over centuries rather than decades. Including fashion images from other datasets can allow researchers to examine additional contexts and mediums that affect changing styles including the influence of advertising through print or digital advertising.

Context: Outfit Analysis. Future research can also include tracking the frequency of the garments worn with baseball-trucker hats to understand the context in which the hats were worn. Looking at the full outfit and garments most often worn with baseball-trucker hats can help with tracking the changing dress codes.

Gender Analysis. Another interesting study would include the investigation of baseball-trucker hat frequency by gender to see if men or women are more likely to wear the hat and to visualize when baseball-trucker hats transitioned into a unisex accessory. Looking at the elements of gender might help with the examination of the role of hats in representing political movements including women's rights.

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APPENDIX

Full Designer List from *Vogue Runway* Dataset 2000-2018

#

1 Piu 1 Uguale 3

1205

3.1 Phillip Lim

3x1

5-Knot

6267

6397

87MM

99%IS

A

A.A. Antonio Azzuolo

A-Cold-Wall

A Degree Fahrenheit

A Detacher

A.F. Vandevorst

A.L.C.

A la Garconne

A.P.C.

A Peace Treaty

A. Sauvage

A.W.A.K.E. MODE

Aalto

Abaete

Abasi Rosborough

Ace & Jig

Acler

Acne Studios

Adam Kimmel

Adam Lippes

Adam Selman

Adeam

Adidas by Stella McCartney

Adriana Degreas

AG

Aganovich

Agi & Sam

Agnes B.

Agnona

Aje

Aka Nanita

Akikoaoki

Akira

Akris

Alabama Chanin

Alberta Ferretti

Alberta Ferretti Limited Edition

Albino

Albino Teodoro

Allbus Lumen

Alchemist

Alejandra Alonso Rojas

Alena Akhmadullina

Alessandra Rich

Alessandro Dell'Acqua

Alex Perry

ALEXACHUNG

Alexander Arutyunov

Alexander Lewis

Alexander Mcqueen

Alexander Terekhov

Alexander Wang

Alexandr Herchcovitch

Alexandre Matthieu

Alexandre Plokhov

Alexandre Vauthier

Alexis Mabille

Alice Auaa

Alice McCall

Alice & Olivia

Alice Roi

Alina Zamanova

Alisa Kuzembaeva

Alistair Carr

Allegra Hicks

Alonova

AltewaiSaome

Altuzarra

Alyx

Ambush

Amg

Ami

Amiri

Amsale

An American View

And Re Walker

And Wander

Andrea Pompilio

Andreas Kronthaler for Vivienne Westwood

Andreeva

Andrew Gn

Andy Debb

Angel Sanchez

Angelos Bratis

Animale

Anja Gockel

Ann Demeulemeester

Ann-Sofie Back Atelje

Anna K

Anna Molinari

Anna October

Anna Sui

Anne Barge

Anne Klein

Anne Sofie Madsen

Anne Valerie Hash

Anouki

Anrealage

Anthony Vaccarello

Anton Belinskiy

Antonio Azzuolo

Antonio Berardi

Antoni Marras

Anya Hindmarch

Aouadi

Apartamento 03

Apiece Apart

Aquascutum

Aquilano.Rimondi

Araisara

Araks

Area

Ariunaa Suri

Arje

Arkadius

Arman Basi One

Armani Prive

Artem Shumov

Artemklimchuk

Arthur Arbesser

As Four

Asger Juel Larsen

Ashish

Ashley Williams

Asian Fashion Meets Tokyo

Assembly

Astrid Andersen

Atelier Kikala

Atelier Versace

Atlein

ATM Anthony Thomas Melillo

Ato

Atsushi Nakashima

Attico

Atto

A Jour Le Jour

Audra

Augustin Teboul

Aula

Avalone

Avtandil

Awaveawake

Azzaro

Azzedine Alaia

B

Babyghost

Back

Badgley Mischka

Baja East

Balenciaga

Bally

Balmain

Banana Republic

Band of Outsiders

Bande Noir

Barbara Bui

Barbara Casasola

Barbara I Gongini

Barbara Tfank

Barre Noire

Bassike

Basso & Brooke

Batsheva

Baum und Pferdgarten

BCBG Max Azria

Beaufille

Beautiful People

Bebe

Beckmans College of Design

Bed j.w. Ford

Behnaz Sarafpour

Bekh

Bella Feud

Belstaff

Benjamin Cho

Bensoni

Berardi

Berluti

Bernhard Willhelm

Bespoken

Bessarion

Betsey Johnson

Betty Jackson

Bevza

Beyond Closet

Bianca Spender

Biba

Bibhu Mohapatra

Big Park

Bill Blass

Billy Reid

Bjorn Borg

Blaak

BlackEyePatch

BLDWN

Bless'ed Are the Meek

Blindness

BLK DNM

Blumarine

Bobkova

Bode

Bodkin

Boglioli

Boris Bidjan Saberi

Bottega Beneta

Bouchra Jarrar

Boudicca

Bourie

Brandon Maxwell

Brandon Sun

Brave Gentleman

Brian Reyes

Brioni

Brock Collection

Brood

Brooks Brothers

Bruce

BrunelloCucinelli

Bruno Pieters

Bruuns Bazaar

Buckler

Buddhist Punk

Burberry Prorsum

By Bonnie Young

By Johnny

By Malene Birger

Byblos

C

C-Neeon

C.P. Company

Cacharel

Cadet

Calla

Callaghan

Calvin Klein

Calvin Klein Collection

Calvin Luo

Camilla Carc
Canali
Capucci
Carin Wester
Carla Zampatti
Carlo Ponti
Carlos Miele
Carmen Marc Valvo
Carmen March
Carolina Herrera
Carven
Casely-Hayford
Cashmere in Love
Catherine Malandrino
CDLM
Cecilie Bahnsen
Cedric Charlier
Celestino Couture
Celine
Central Saint Martins
Cerre
Cerruti
Cerruti 1881
CF Goldman
CG
Chadwick Bell
Chaiken
Chakshyn
Chalayan
Chanel
Charles nastase
Charles Jeffrey Loverboy
Ccharles Nolan
Charlotte Olympia
Charlotte Ronson
Charms
Cheap Monday
Cher Michel Klein
Chika Kisada
Childs
Chloe
Chloe Sevigny for O.C.
Chris Benz
Christian Cota
Christian Cowan
Christian Dada
Christian Dior
Christian Lacroix
Christian Siriano
Christian Wijnants
Christophe Lemaire
Christopher Esber
Christopher Kane
Christopher Raeburn
Christopher Shannon
Chromat
Chufy
Cienne
Cinq as Sept
Cividini
Claudia Li
Clements Ribeiro
Cloak
Clover Canyon
Club Monaco
CMMN SWDM
Co
Coach
Colcci
Collette Dinnigan
Collina Strada
Colovos
Comme des Garcons
Comme des Garcons Homme Plus
Comme des Garcon Sshirt
Commonwealth Utilities
Commuun
Comptoir des Cotonniers
Conny Groenewegen
Coperni Femme
Corneliani
Costello Tagliapietra
Costume National

Cotoo
Cottweiler
County of Milan
Courreges
Coven
Craig Green
Creative Taiwan
Creatures of Comfort
Creatures of Wind
Cres. E Cim.
Crippen
Curated by Ek Thongprasert
Cushnie
Cushnie et Ochs
Custo Barcelona
Cut25 by Yigal Azrouel
Cynthia Rowley
Cynthia Steffe

D

D & G
Dagmar
Dailyroutine
Daks
Daks by Giles Deacon
Dalood
Damir Doma
Daniel Vosovic
Daniel W. Fletcher
Danielle Frankel
Danielle Scutt
Daryl K
Dasha Gauser
Datuna
Datuna Sulikashvili
Daughters
David Catalan
David Hart
David Koma
David Michael
Davidelfin
Dax Gabler
Day Birger et Mikkelsen
Dean Quinn
Death To Tennis
Deceive
Delpozo
Dennis Basso
Derek Lam
Derek Lam 10 Crosby
Derercuny
Designers Remix
Deveaux
Devi Kroell
Devon Halfnight Leflufy
Dgnak
Diana orving
Diane von Furstenberg
Dice Kayek
Diesel
Diesel Black Gold
Dietrich Emter
Dimaneu
Dimitri
Dion Lee
Dior Homme
Dirk Bikkembergs
Dirk Schonberger
Discount Universe
Discovered
Djaba Diassamidze
DKNY
DMDV
Dolce & Gabbana
Domanoff
Dondup
Donna Karan
Doo.Ri
Double Rainbouu
Doublet
Douglas Hannant
Drag + Drop
Dress Co
Dresscamp
DressedUndressed
Dries Van Noten
Dsquared2

Duckie Brown
Dundas
Dunhill
Duro Olowu
Dyn
Dyne
Dzhus

E

E.Tautz
Each x Other
Eckhaus Latta
Edeline Lee
Editions MR
Ddun
Elder Statesman
Electric Feathers
Elena Burba
Elena Burenina
Elena Rial
Elenareva
Eley Kishimoto
Eleykishimoto
Ellesse
Elie Saab
Elie Tahari
Elise Verland
Elizabeth and James
Elizabeth Kennedy
Ellen Tracy
Ellery
Eloshi
Elspeth Gibson
Emanuel Ungaro
Emelie Janrell
Emilia Wickstead
Emilio de la Morena
Emilio Pucci
Emma Cook
Emma Mulholland
Emporio Armani
Enfants Riches Deprimes
Engineered Garments
Erdem
Eric Bergere
Eric Schlosberg
Erika Cavallini
Erin Retherston
Erin Wasson x RVCA
Ermanno Scervino
Ermenegildo Zegna
Escada
Esteban Cortazar
Esther Perbandt
Et Momonakia
Ethosens
Etoile Isabe Marant
Etro
Etudes
Etw.Vonneguet
Eudon Choi
Everlasting Sprout

F

Facetasm
Factotum
Faith Connexion
Farah Angsana
Fashion East
Fashion Fringe
Faustine Steinmetz
Fausto Puglisi
Fay
Fear of God
Felder Felder
Felipe Oliveira Baptista
Fendi
Feng Chen Wang
Fenty Puma
Feraud
Filippa K
Filippa K Man
Filles a Papa
Flannel
Fleamadonna
Flow the Label
Fonnesbech
For Restless Sleepers
Frame Denim

Francesc by Frank Tell

Francesco Scognamiglio

Frank Tell

Treiknock

Freya Dalsjo

Frolov

FrostFrench

Fumito Ganryu

Fur Fur

G

G-Star

G.V.G.V.

Gabriela Hearst

Gabriele Colangelo

Gabrielle Greiss

Gail Sorronda

Galia Lahav

Galvan

Ganni

Ganryu

Gant by Michael Bastian

Gap

Gardem

Gareth Pugh

Gary Bigeni

Gary Graham

Gasanova

GCDS

Generra

Genny

George Amirejibi

George Keburia

George Pantsulaia

Giada

Giamba

Giambattista Valli

Gianfranco Ferre

Gibo

Gibsh

Gieves Hawkes

Gilded Age

Giles Deacon

Ginger Smart

Giorgio Armani

Giuliana Romanno

Giulietta

Givenchy

Gloria Coelho

GmbH

Goga Nikabadze

Gola Damian

Gosha Rubchinskiy

Graeme Armour

Graeme Black

Greg Lauren

Gregory Parkinson

Greta Constantine

Greta Gram

Grey Jason Wu

Growing Pains

Gryphon

Gucci

Gudu

Gulcin Cengel

Guo Pei

Gustav Von Aschenbach

Gut's Dynamite Cabarets

Guy Laroche

Gypsy Sport

H

H&M Design Award

Habitual

Haider Ackermann

Hakaan

Halpern

Halston

Halston Heritage

Hamish Morrow

HAN

Han Ahn Soon

Han Kjobenhavn

Hanae Mori Designed by Yu Amatsu

Haney

Hanii Y

Hannah Marshall

Hardy Amies

Hare

Harmon

Haryono Setiadi

Haus Alkire

Heatherette

Hecho

Heich Es Heich

Helbers

Hellessy

Helmut Lang

Helo Rocha

Henrik Vibskov

Hensely

Heohwan Simulation

Hermes

Hernandez Cornet

Heron Preston

Herve Leger

Herve Leger by Max Azria

Hien Le

Hillier Bartley

H&M

Holiday Boileau

Holly Fulton

Holmes & Yang

Holzweiler

Honor

Hood By Air

Hope

Houghton

House of Holland

House of Jazz

Hugo

Hugo Boss

Huishan Zhang

Hunkydory

Hunter Original

Hutson

Hyke

I

Icarius de Menezes

ICB

Iceberg

Ida Klamborn

Ida Sjostedt

Ienki Ienki

Imitation of Christ

Inbal Dror

Inshade

Io Ipse Idem

Ioana Ciolacu

Iris Van Herpen

Iro

Isa Arfen

Isaac Mizrahi

Isabel Marant

Isabell de Hillerin

Isola Marras

Issa

Issever Bahri

Issey Miyake

Istvan Francer

Ivan Grundahl

Ivanman

Ivka

J

J Brand

J Crew

J.JS Lee

J. Kim

J Koo

J. Lindeberg

J. Mendel

JW Anderson

Jacquemus

Jaeger London

Jahnkoy

Jain Song

James Coviello

James Long

Janashia

Jardin Exotique

Jarret

Jasmin Shokrian

Jasmin Shokrian Draft No. 17

Jasmine Di Milo

Jason Wu

Jasper Conran

Jay Ahr

Jayson Brunsdon

JC de Castelbajac

Jealousy

Jean Colonna

Jean Gritsfeldt

Jean Paul Gaultier

Jean-Pierre Braganza

Jeffrey Chow

Jeffrey Dodd

Jeffrey Rudes

Jen Kao

Jenni Kayne

Jenny Packham

Jens Laugesen

Jeremy Jaing

Jeremy Scott

Ji Oh

Jil Sander

Jil Sander Navy

Jill Stuart

JNBY

Joe Casely-Hayford

Johan Ku

Johanna Ortiz

John Bartlett

John Elliot

John Galliano

John Lawrence Sullivan

John Richmond

John Rocha

John Varvatos

Joie

Jonathan Cohen

Jonathan Saunders

Jonathan Simkhai

Joseph

Joseph Abboud

Josh Goot

Josie Natori

Jourden

Jovovich Hawk

Joy Cioci

Jsen Wintle

Juan Carlos Obando

Juicy Couture

Julia Nikolaeva

Julia Seemann

Julian Louie

Julian Zigerli

Julien David

Julien MacDonald

Julius

Jun Okamoto

Junya Watanabe

Just Cavalli

Juunj

K

Kaal E.Suktae

Kaelen

Kai Kuhne

Kamishima Chinami

Kanye West

Kanye West Adidas Originals

Karen Walker

Karl Lagerfeld

Karl Lagerfeld for Riachoelo

Karla Spetic

Karolina Zmarlak

Katama

Katayone Adeli

Kate Spade New York

Kate Sylvester

Katerina Kvit

Katie Eary

Katie Ermilio

Katie Gallagher

Katy Rodriguez

Kaufmanfranco

Kaviar Gauche

Keanan Duffty

Keita Maruyama

Kelly Wearstler

Kendall + Kylie

Kenneth Cole Collection

Kenneth Cole-New York

Kent & Curwen

Kenzo

Kenzo La Memento

Kes
Kevork Kiledjian
Khaite
Khomenko + Zirochka
Kiko Kostadinov
Kilgour
Kilian Kerner
Kim Jones
Kim Shui
Kimberly Ovitz
Kimseoryong
Kinder Aggugini
Kiok
Kith
Kiton
Kitx
Kimora Lee Simmons
Koche
Koi Suwannagate
Kolor
Kozaburo
Kris Van Assche
Krizia
Krizia Top
Krystof Strozyna
Ksenia Knyazeva
Ksenia Schnaider
Ksenia Seraya
KTS
Kuzyomin
Kwaidan Editions
Kye

L

L.A.M.B.
L'Wren Scott
La DoubleJ
La Perla
La Vie Rebecca Taylor
Lacoste
Lado Bokuchava
L'Agence
Lagerfeld Gallery
Lake Stars
Lake Studio
Lako Bukia
Lala Berlin
Lalo
Landlord
Lanvin
Laquan Smith
Larisa Lobanova
Laura Garcia
Laura Siegel
Laurel
Lawrence Steele
Lazoschmidl
Le Kilt
Lee Mathews
Lee Roach
Lein
Lela Rose
Lemlem
Lena Hoschek
Lenny Niemeyer
Leonard
Les Benjamins
Les Copains
Les Hommes
Les Homme
Libertine
Lie Sang Bong
Lilly Sarti
Limi Feu
Linder
Lindsey Thornburg
Lisa Marie Fernandez
Lisa Perry
Litkovskaya
Lizzy Disney
Local Firm
Loden Dager
Loewe
Lolitta
London Roundup
Longchamp
Lorod
Lou Dallas
Lou Dalton
Louis Vuitton

Louise Friedlaender

Louise Goldin

Louise Gray

Low Classic

LP.BG

LRS

Luar

Luca Luca

Lucas Nascimento

Lucien Pellat Finet

Lucio Vanotti

Lucky Chouette

Ludovic de Saint-Sernin

Luella

Luisa Beccaria

Lulu & Co

Lumier Garson

Lutz Huelle

Lutz & Patmos

Lyn Devon

M

M. Martin

M Missoni

M.PATMOS

M.R.S.

Mach&Mach

Madewell

Mads Norgaard

Maggie Marilyn

Maid in Love

Maison Francesco Scognamiglio

Maison Kitsune

Maison Martin Margiela

Maison Mayle

Maison Mihara Yasuhiro

Maison Rabih Kayrouz

Maiyet

Maje

Maki Oh

Malaikaraiss

Malibu 1992

Malo

Mame

MAN

Mandy Coon

Manish Arora

Mansur Gavriel

Mantis Religiosa

Mara Hoffman

Marc by Marc Jacobs

Marc Jacobs

Marc Jacobs Men

Marcel Ostertag

Marchesa

Marchesa Notte

Marchesa Voyage

Marco de Vincenzo

Margaret Howell

Maria Grachvogel

Marianna Senchina

Marina Hoermanseder

Marina Moscone

Marine Serre

Marios Schwab

Marissa Webb

Marjan Pejoski

Mark Eisen

Mark Fast

Mark Kenly by Domino Tan

Mark McNairy New Amsterdam

Markus Lupfer

Marni

Marques'Almeida

Marta Jakubowski

Martin Grant

Martine Rose

Martine Sitbon

Mary Katrantzou

Mary Ping

Maryam Nassir Zadeh

Maryling

Marysia

Masterpeace

Materiel

Materiel by Aleksander Akhalkatsishvili

Materiel by Tiko Paksashvili

Maticevski

Matohu

Matt Nye

Matthew Adams Dolan

Matthew Ames

Matthew Miller

Matthew Williamson

Matty Bovan

Maurizio Pecoraro

Max Azria

Max Mara

Max Mara Atelier

Maxime Simoens

McQ Alexander McQueen

Meadham Kirchhoff

Mehtap Elaidi

Melitta Baumeister

Meltem Ozbek

Menichetti

Mercibeaucoup

Miaou

Michael Angel

Michael Bastian

Michael Kors Collection

Michael Lo Sordo

Michael Sontag

Michael van der Ham

Michelle Lowe Holder

Michon Schur

Miguel Adrover

Miharayasuhiro

Mihara Yasuhiro Modified

Mikio Sakabe

Milly

Minju Kim

Mint Designs

Mira Mikati

MISBHV

Miss Gee Collection

Miss Sixty

Miss Wu

Missoni

Miu Miu

MM6 Maison-Martin Margiela

MM6 Maison Martin Margiela x Opening Ceremony

Modernist

Molly Goddard

Moncler 1 Pierpaolo Piccioli

Moncler 2 1952

Moncler 3 Grenoble

Moncler 4 Simone Rocha

Moncler 5 Craig Green

Moncler 6 Kei Ninomiya

Moncler Noi Kei Ninomiya

Moncler 7 Fragment Hiroshi Fujiwara

Moncler 8 Palm Angels

Moncler Gamme Bleu

Moncler Gamme Rouge

Moncler Grenoble

Monique Lhuillier

Monse

Moohong

Moon Choi

Moschino

Moschino Cheap-Chic

Mother

Mother of Pearl

Moto Guo

Motohiro Tanji

Motonari Ono

MP Massimo Piombo

Mr Gentleman

MSGM

Mugler

Mulberry

Munn

Munsoo Kwon

Murral

MYAR

Myrza de Muynck

N

N.Hoolywood

Nabil Nayal

Nadya Dzyak

Naeem Khan

NAHM

Namacheko

Name.

Nanette Lepore

Nanushka

Naoki Takizawa

Narciso Rodriguez

Nashe

Nasir Mazhar

Natasha Zinko

Nathan Jenden

Naum

Nautica

Navro

Ne-Net

Nehera

Neil Barrett

Nellie Partow

Nells Nelson

Nhorm

Nicholas K

Nicholas Nybro

Nicolas Andreas Taralis

Nicolas Grigorian

Nicole Farhi

Nicole Miller

Nicopanda

Nili Lotan

Nina Donis

Nina Ricci

Nino Babukhadia

Nitz Schneider

No. 21

No. 6

Noa Raviv

Nohke

Noir

Noir Kei Ninomiya

Nomia

Nonoo

Norma Kamali

Novis

Nozomi Ishiguro Tambourine

Number (N)ine

NYC 2000

O

Oak

OAMC

Obedient Sons & Daughters

Objects Without Meaning

Odeur

Off-White

Officine Generale

Ohne Titel

Oliver Spencer

Olivier Theyskens

Olympia Le-Tan

Omelya

Opening Ceremony

Ordinary People

Organic by John Patrick

Orla Kiely

Orley

Oscar de la Renta

Osklen

Osman

Ossie Clark

Cstel

Ostwald Helgason

Ottolinger

Oumlil

Our Legacy

Outlaw

Ovadia & Sons

Ozgur Masur

Ozlem Kaya

P

Paco Rabanne

Pal Zileri

Palm Angels

Palme Harding

Palmiers du Mal

Palomo Spain

Palson Kifot

Pam & Gela

Pamela Dennis

Pamella Roland

Paola Raia

Paper London

Paria Farzaneh

Paris 68

Parsons MFA

PatBo

Patricia Viera

Patrik Ervell

Paul & Yakov

Paul & Joe

Paul Smith

Paula Raia

Paule Ka

Pedro del Hierro Madrid

Pedro Lourenco

Perret Schaad

Perry Ellis

Perry Ellis by Duckie Brown

Petar Petrov

Peter Jensen

Peter Pilotto

Peter Som

Peter Soronen

PH5

Phelan

Phenomenon

Phi

Philip Treacy

Philipp Plein

Philosophy

Phoebe English

Phoenix Keating

Piazza Sempione

Piece d'Anarchive

Pierre Balmain

Pierrot

Pieter

Pigalle

Piombo

Pirosmani

Plan C

Plastic Yokyo

Poiret

Pollini

Polo Ralph Lauren

Porsche Design

Portnoy Beso

Ports 1961

Poustovit

Poustovit x Tago

PPQ

prabal- Gurung

Prada

Preen by Thornton Bregazzi

Preen Line

Pringle of Scotland

Priscavera

Prism

Proenza Schouler

Project Alabama

Protagonist

Public School

Pushbutton

Pyer Moss

R

R II S

R13

Rachel Antonoff

Rachel Comey

Rachel Roy

Rachel Zoe

Rad by Rad-Hourani

Rad Hourani

Raf Simons

Rafael Lopez

Rag & Bone

Rahul Mishra

Rake

Ralph & Russo

Ralph Lauren
Ralph Rucci
Ralph Rucci Chado
Randolph Duke
Raquel Allegra
RCR Khomenko
Rebecca Danenberg
Rebecca de Ravenel
Rebecca M inkoff
Rebecca Taylor
Rebekka Ruetz
Red Valentino
Redemption
Re/Done
Reed Krakoff
Reem Acra
Reinaldo Lourenco
Rejina Pyo
Rena Lange
Requiem
Revillon
Reyes
Rhie
Ria Keburia
Riccardo Tisci
Richard Chai
Richard Chai Love
Richard Edwards
Richard James
Richard Malone
Richard Nicoll
Richard Quinn
Richard Tyler
Rick Owens
Rito
Robert Cary - Williams
Robert Geller
Robert Rodriguez
Roberto Cavalli
Rochambeau
Rochas
Rock Republic
Rocket x Lunch
Rodarte
Rodebjer
Rodnik
Rogan
Roggykei
Roksanda
Roland Mouret
Roland Mouret Mr.
Romance Was Born
Ronald van der Kemp
Roopa Pemmaraju
Rosetta Getty
Rosie Assoulin
Rossella Jardini
The Row
RR331
Rshemiste
RTA
Ruban
Rue du Mail
Ruffian
Ruffo Research
Russell Sage
Ryan Lo
Ryan Roche
Rykiel Homme

S

Sabyasachi
Sacai
Sacai Luck
Sachi & Babi
Saint Laurent
Saint-Tokyo
Saks Potts
Salle De Mode
Sally LaPointe
Sally Penn
Saloni
Salvatore Ferragamo
Samuji
Sand
Sandra Mansour
Sandro
Sandy Liang
Santoni Edited by Marco Zanini

Sara Battaglia
Sari Gueron
Sasha Kanevski
Sass Bide
SB47
Schiaparelli
Schumacher
Scotch & Soda
Sea
Sean John
Sebastian Pons
Section 8
See by Chloe
Selam Fessahaye
Self-Portrait
Seredin & Vasiliev
Shaina Mote
Sharon Wauchob
Shaun Samson
Shelley Fox
Shipley Halmos
Shiroma
Shrimps
Shushan
Sibling
Sid Neigum
Sies Marjan
Siki Im
Silvia Tcherassi
Simon Miller
Simon Spurr
Simone Rocha
Simonetta Ravizza
Sinha-Stanic
Sister by Sibling
situationist
SJYP
Slava Zaitsev
Snow Xue Gao
Solace London
Somarta
Sonia by Sonia Rykiel
Sonia Rykiel
Sophia Kah
Sophia Kokosalaki
Sophie Theallet
Sophomore
Sopopular
Sorry I'm Not
Sportmax
Sretsis
Sss World Corp
St. John
St. Roche
Stand
Steinrohner
Stella Jean
Stella McCartney
Stephan Pelger
Stephen Burrows
Steve J & Yoni P
Steven Alan
Stine Goya
Stone Fox Bride
Strateas Carlucci
Strenesse
STRK
Studio Heijne
Suboo
Subrosa
Sue Stemp
Sulvam
Sunnei
Suno
Supercomma B
Surface to Air
Susan Lazar
Suzanne Rae
Swedish Fashion Talents
Swedish School of Textiles
Sweetface
Sykes
SYZ

T

T by Alexander Wang
Taakk
Tabula Rasa
Tadashi Shoji
Tae Ashida
Takahiromiyashi the Soloist
Takeo Kikuchi

Tako Mekvabidze
Talbot Tunhof
Talbots
Tamara Mellon
Tamuna Ingorokva
Tanya Taylor
Tao
Tatuna Nikolaishvili
Teatum Jones
Telfar
Temperley London
Ter et Bantine
Tess Giberson
Tessa
Thaddeus O'Neil
Thakoon
Thakoon Addition
The Coat by Katya Silchenko
The Gigi
The Great
The Kooples
The Sirius
Theo
Theory
Theyskens Theory
Thimister
Thom Browne
Thomas Tait
Threeasfour
Tia Cibani
Tibi
Tiger of Sweden
Tiit
Tim Coppens
Tim Hamilton
Tim Hamilton Redux
Tim van Steenbergen
Timo Weiland
TL-180
Tocca
Tod's
Todd Lynn
Todd Snyder
Toga
Tokyo New Age
Tom Ford
Tomas Maier
Tome
TOMMY
Tommy Hilfiger
Toni Maticevski
Tonsure
Tony Melillo
Topman Design
Topshop Unique
Tory Burch
Tory Sport
Tosia
Toteme
tracy Reese
Trademark
Trager Delaney
TRE by Natalie Ratabesi
TRIAS
Tribune Standard
Trina Turk
Triple RRR
Tristan Webber
Ttriya
Trovata
Trussardi
TSE
Tsumori Chisato
Tucker
Tuleh
Turbo ulia
Twenty8 Twelve
Tyler
Tze Goh

U

U.G.LY
Ujoh
Ulla Johnson
Ulyana Sergeenko
Umit Benan
Undercover
Ungaro Couture
Uniqueness
United Bamboo

Unravel

Urban Zen

Uri Minkoff

Use Unused

V

V by Gres

Vahan Khachatryan

Valentin Yudashkin

Valentino

Valery Kovalska

Vanessa Bruno

Vanessa Seward

Vanishing Elephant

Vaquera

Vejas

Vektor

Vena Cava

Vera Wang

Vera Wang Lavender Label

VeronicaVB. Ballenes

Veronica Beard

Veronique Branquinho

Veronique Leroy

Verrier

Versace

Versus Versace

JW Anderson Collection

Vetements

Vfiles

Victor Alfaro

Victor Glemaud

Victoria Beckham

Victoria by Victoria Beckham

Victoria Victoria Beckham

Vika Gazinskaya

Vikto & Rolf

Vilshenko

Vince

Vionnet

Vipers

Visvim

Vitorino Campos

Viva Vox

Vivetta

Vivienne Tam

Vivienne Westwood

Vix

Vladimir Karaleev

Vozianov

VPL

W

Wales onner

Walter Van Beirendonck

Wanda Nylon

Warm

Warren Noronha

Wayne

WC

We Are Handsome

Weannabe

Wendelborn

Wendy Nichol

Wes Gordon

Whistles

Whit

White Mountaineering

Whiz Limited

Who Is It?

Who Is on Next

Whyred

William Rast

Willow

Willy Chavarria

Wink

Wolk Morais

Wood Wood

Woolrich Woolen Mills

Wooyoungmi

Wren

WrittenAfterwards

Wunderkind

X

Xuly.Bet

Y

Y-3

Y/project
Yang Li Yasutoshi
Yajun

YCH
Yeohlee
Yigal Azrouel
Yinging Yin
Yohei Ohno
Yohji Yamamoto
Yoko Devereaux
Yoshio Kubo
Yulia Nikolaeva
Y s
You As
Yulia
Yulia Yefimtchuk
Yuliya Polishchuk

Z

Zero + Maria
Cornejo

Zeynep Tosun

Zimmermann

Zirochka Ukraine

Zoe Jordan

Z Zegna

Zac Posen

ZAC Zac Posen

Zachary Prell
Zadig & Voltaire
Zambesi
ZDDZ